Available online at https://asric.africa/engineering-sciences
ASRIC Journal on Engineering Sciences Vol.4(1)(2023) 88-97

# Seizure Pattern Recognition Using Fast Walsh Hadamard (FWHT) Transform

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**Abstract**

Epileptic seizure detection is an emerging approach to the neurological processing of brain signals. Previously, recognition of epileptic seizures has been done from visual scanning of EEG signals by expert neurologists into various categories such as healthy and fatigue epochs. Unfortunately, this procedure is not effective because it is exhausting, time consuming and generally leads to incorrect results. Therefore, specialists found that automatic seizure detection a more effective technique for diagnosing. In this paper, we demonstrate an automated method for detection of abrupt changes of Electro-Encephalogram (EEG) signals depending on usage of FAST Walsh Hadamard Transform (FWHT). The FWHT analyzes the EEG signals in the frequency domain and decomposes it into the Hadamard coefficients. Different signal attributes are extracted from the decomposed EEG signals. These attributes comprise: band power Beta, band power Delta, band power Gamma, band power Theta and finally mean curve length (MCL) attribute. Finally, classification is implemented using a thresholding strategy to discriminate between seizure and healthy epochs. This method is tested on long-term EEG recordings from the available Physio-Net EEG dataset. The proposed method demonstrates a high classification performance in comparison with other previous methods. An average sensitivity of 94.54%, an average specificity of 95.2% and an average accuracy of 96.1363% are achieved from the mean curve length feature with FWHT.

**Keywords**: EEG, epilepsy, seizure detection and FWHT

## 1. Introduction

Electroencephalography is a medical signal acquisition system, which is utilized to read scalp electrical activities resulting from various brain functions. The electroencephalogram (EEG) in a simple word that refers to the recording of electrical activities, which contain useful information of different human states. Therefore, these recordings not only can be used to diagnose various brain disorders such as Alzheimer's disease and epilepsy, but it can also be used to monitor patterns of consciousness (such as feelings and emotions) or unconsciousness (such as sleep state and comma) of a human. [1, 2]. Specialists have shown that epilepsy characterization is the most prevalent and dominant in the field of processing of electrical EEG signals [3].

Epilepsy is one of the most serious, acute and chronic brain disorders that cause an imbalance in the human nervous system. It should be noted that epilepsy patients face many challenges and risks in their daily lives, especially when dealing with heavy machinery or driving vehicle, due to the loss of control over most of the nervous organs [4]. Recent studies have shown that approximately more than 65% of epilepsy patients can control seizures through anti-epileptic drugs, and approximately 10% could befit from surgery. The remaining 25% have drug resistant and experience sudden symptoms. Therefore, it is necessary to notify the patient's medication-resistant epileptic seizure to the caretaker and analyze the pattern of related signals before, during, and after the seizure onset [5].

The most effective method for epileptic activity analysis among diagnostic imaging methods is the analysis of electrical EEG signals. These signals give a description of the voltage fluctuations, which result from ionic current within the brain [6]. Hence, there was a need for seizure detection and seizure prediction strategies, where seizure detection deals with recognition of seizures that occurring (or have occurred) through analysis of biologic signals recorded from a patient with epilepsy.

The rest of this paper is organized as follows. Section 2 presents the description of experimental materials and utilized methods. This section includes a brief description of the FWHT algorithm, the EEG signal attributes and the performance metrics. Section 3 investigates the simulation results and discussion. Finally, section 4 gives the conclusion remarks.

## 2. Materials and Methods

### 2.1 Description of the Dataset

To evaluate the proposed approach, we used the online CHB-MIT dataset, which was acquired at the Children Hospital Boston. It is also referred to as the Physio Net EEG dataset [7], which is composed of EEG recordings for pediatric individuals with intractable seizures. These recordings are public, available, and widely-used in the detection and prediction of epileptic seizures. It is grouped into 23 cases with various genders and different ages. It contains5 males, ages 3–22; and 17 females, ages 1.5–19. The standard 10-20 electrode system has been used to collect the EEG recordings in this dataset, which is sampled with a sampling rate of 256 Hz. The brief description of these datasets is illustrated in table 1. This table includes all cases of patients, showing their age, gender and number of seizures for each case, in addition to the time taken during the measurement.

**Table 1. Cases considered for seizure detection on CHB-MIT dataset [7].**

| Patient no. | Gender | Age | Seizure |
|---|---|---|---|
| 1 | F | 11 | 3 |
| 2 | M | 11 | 7 |
| 3 | F | 14 | 4 |
| 4 | M | 22 | 5 |
| 5 | F | 7 | 10 |
| 6 | F | 15 | 3 |
| 7 | F | 14.5 | 5 |
| 8 | M | 3.5 | 4 |
| 9 | F | 10 | 7 |
| 10 | M | 3 | 3 |
| 11 | F | 12 | 7 |
| 12 | F | 22 | 10 |
| 13 | F | 3 | 8 |
| 14 | F | 9 | 20 |
| 15 | M | 16 | 8 |
| 16 | F | 7 | 3 |
| 17 | F | 12 | 6 |
| 18 | F | 18 | 3 |
| 19 | F | 19 | 8 |
| 20 | F | 6 | 4 |
| 21 | F | 13 | 3 |
| 22 | F | 9 | 7 |
| 23 | F | 6 | 7 |
| 24 | F | - | 16 |

### 2.2 Proposed Method

The proposed method depends mainly on the FWHD for discrimination between seizure and healthy epochs. The main idea of the proposed method is based on the decomposition of EEG signals into Hadamard coefficients, and then extraction of a certain attribute from decomposed EEG signals. Finally, the classification stage is performed based on a feature ranking method with a single attribute statistic as shown in Fig.1. In this method, the Receiver Operating Characteristic (ROC) curve is utilized for performance assessment according to the selected attribute. The ROC curve is a relation between sensitivity and 1-specificity, for various values of the threshold. Ranking in general is executed depending on the area under the ROC curve [8, 9, 10]

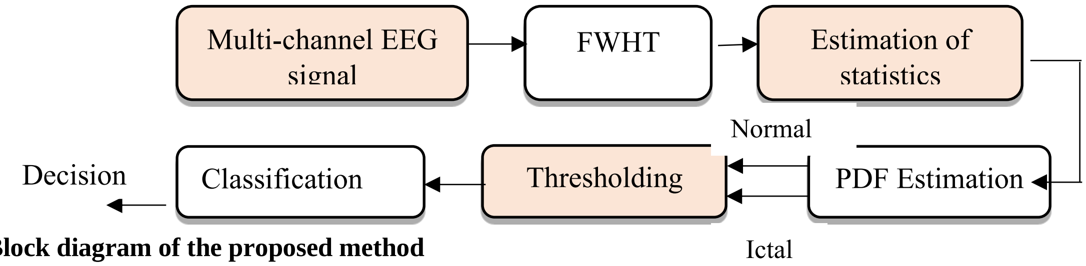



**Fig.1: Block diagram of the proposed method**

The detection results are obtained for a selected attribute. The considered attributes include band power of brain waves including (Beta, Alpha, Theta, Gamma and Delta) and mean curve length are estimated for decomposed Hadamard coefficients. The classification strategy is performed based on a thresholding technique in which an optimum threshold is determined first on each attribute after PDF estimation of normal and seizure epochs, and then the threshold used in the classification process. Each threshold value is obtained at the intersection point between two PDF curves for normal and seizure activities as illustrated in Fig.3. The distributions are obtained for groups of segments for normal and seizure activities to obtain the PDFs of FWHT coefficients. We clarify the values of thresholds for all attributes for all cases of CHB-MIT dataset in Tables 3 to 8 utilizing MATLAB code as shown in Fig.2

```
% Calculating the threshold values between the data points
s_data = unique(sort(data(:)));      % Sorted data points
d_data = diff(s_data);               % Difference between consecutive po
if(isempty(d_data)), error('Both class data are the same!'); end
d_data(length(d_data)+1,1) = d_data(length(d_data));% Last point
thres(1,1) = s_data(1) - d_data(1);              % First point
thres(2:length(s_data)+1,1) = s_data + d_data./2; % Threshold values

% Sorting each class
if(mean(data(:,1))>mean(data(:,2))), data = [data(:,2),data(:,1)]; end

% Calculating the sensibility and specificity of each threshold
curve = zeros(size(thres,1),2);
distance = zeros(size(thres,1),1);
for id_t = 1:1:length(thres)
    TP = length(find(data(:,2) >= thres(id_t)));   % True positives
```

```
% Calculating the sensibility and specificity of each threshold
curve = zeros(size(thres,1),2);
distance = zeros(size(thres,1),1);
for id_t = 1:1:length(thres)
    TP = length(find(data(:,2) >= thres(id_t)));   % True positives
    FP = length(find(data(:,1) >= thres(id_t)));   % False positives
    FN = L - TP;                                   % False negatives
    TN = L - FP;                                   % True negatives

    curve(id_t,1) = TP/(TP + FN);   % Sensitivity
    curve(id_t,2) = TN/(TN + FP);   % Specificity

    % Distance between each point and the optimum point (0,1)
    distance(id_t)= sqrt((1-curve(id_t,1))^2+(curve(id_t,2)-1)^2);
end
```

**Fig.2** MATLAB code for determination of threshold

The EEG seizure detection performance based on a single attribute is evaluated depending on five important metrics, which are optimum threshold Sensitivity (SEN), optimum threshold Specificity (SPE), obtained maximum Accuracy (ACC), Positive Predicted Value (PPV), Negative Predicted Value (NPV). These results are given in Tables 3to 6. The steps of the proposed method are illustrated in Algorithm 1 for the detection of normal and seizure activities for epilepsy patients.

**Algorithm (1).**

Detection of normal and seizure activities for epilepsy patients

Input: Multi-channel EEG signal.

Procedure:

1- Apply FWHT on EEG signals.
2- Study the effect of the various brain wave bands including beta, delta, gamma and theta for several normal and seizure waveforms.
3- Extract band power attribute from decomposed EEG coefficients for several normal and seizure waveforms.
4- Estimate PDFs of the selected attribute for several normal and seizure waveforms.
5- Estimate the intersection point of the PDFs.
6- Apply a ranking step for new incoming segments to perform classification.
7- Obtain ROC curve and calculate area under ROC curve
8- Obtain SEN, SPE, ACC, PPV, and NPV for all segments.

Output: ACC and FAR

### 2.2.1 Fast Walsh Hadamard Transform (FWHT)

The FWHT is an efficient methodology, which depends mainly on transformation of signals from time domain to frequency domain. It is worth monitoring that Walsh Hadamard transform is defined as being sequence oriented [11]. In addition to providing spectral representation, Hadamard transform is also essential for describing certain types of systems and their properties in the frequency domain. It has a high efficiency to identify the signals that have sharp disturbances in a more accurate way [12]. The FWHT of a signal $x(n)$ for $n= 1, 2, \ldots\ldots N$ can be computed according to this equation.

$$X_w(k) = \sum_{n=1}^{N} x(n) W_n \quad , \ k = 1,2, \ldots\ldots N \qquad (1)$$

where N indicates the total number of samples and Wn represents the Walsh matrix, which is given by the following equation:

$$W_n = \frac{1}{2^{\frac{n}{2}}} \begin{pmatrix} W_{n-1} & W_{n-1} \\ W_{n-1} & -W_{n-1} \end{pmatrix} \qquad (2)$$

The basic benefit of this transformation is the high speed in performance, and it requires less storage memory to store decomposed coefficients.

### 2.2.2 EEG Signal Attributes

- **Band Power Attribute**

Band power attribute represents the power or the energy of EEG signals for a given frequency band in a given channel, averaged over a given time window (typically 1 second for many Brains Computer Interface (BCI) paradigms). Typically, there are various kinds of bands of EEG power including; Delta (0.5-4Hz), Theta (4-8Hz), Alpha (8-12Hz), Beta (12-30Hz), and Gamma (30-45Hz) as shown in Fig.4 [13]

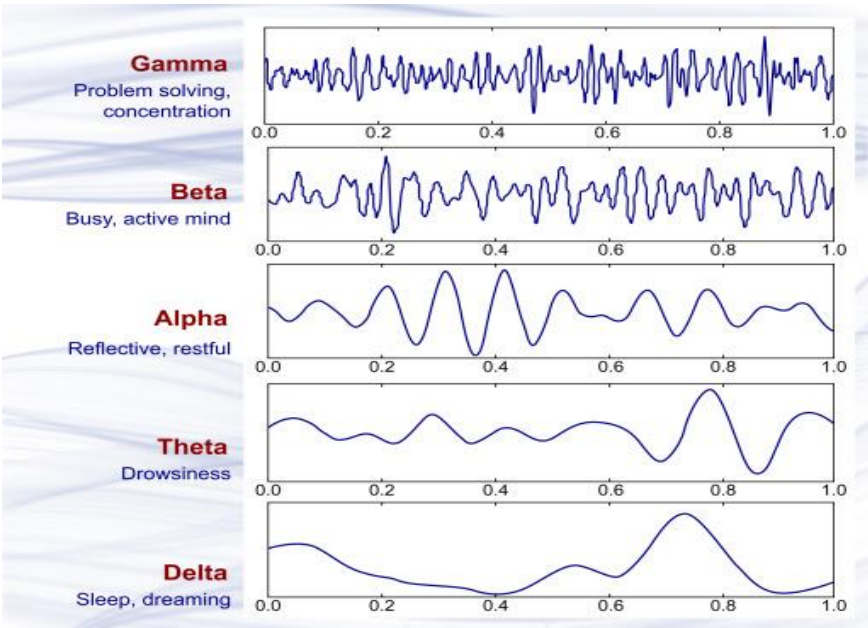



**Fig. 4** Brain waves samples in one second [13]

- **Mean Curve Length (MCL)**

It is one of the prominent features in the field of recognition of EEG signals, as it reduces the computational cost and leads to better performance. It provides a measure of signal complexity depending on Katz fractal dimension [14]. The Curve Length (CL) can be defined as the sum of linear distances between successive points on the curve. In the case of EEG signals, it can be defined for a time series as the sum of the absolute value of the first order finite difference. The MCL can be determined as the average of CL values. The MCL of a signal $x(n)$ for length $N$ can be obtained according to the following equation:

$$MCL = \frac{1}{N-1}\sum_{n=0}^{N-2} |x(n+1) - x(n)| \qquad (5.7)$$

### 2.2.3 Performance Metrics

The performance of the proposed method is evaluated depending on six metrics as follows [15] as tabulated in Table .2

**Table 2. Performance metrics of the proposed approach**

| Performance Metric | Equation |
|---|---|
| Sensitivity (SEN %) | $\boldsymbol{SEN = \frac{TP}{TP+FN} \times 100}$ (7) |
| Specificity (SPE %) | $\boldsymbol{SPE = \frac{TN}{TN+FN} \times 100}$ (8) |
| Accuracy (ACC %) | $\boldsymbol{ACC = \frac{TP+TN}{TP+TN+FP+FN)} \times 100}$ (9) |
| Positive Prediction Value (PPV %) | $\boldsymbol{PPV = \frac{TP}{TP+FP} \times 100}$ (10) |
| Negative Prediction Value (NPV %) | $\boldsymbol{NPV = \frac{TN}{TN+FN} \times 100}$ (11) |
| ROC | It is created by plotting sensitivity versus 1-specificity at various values of the threshold. |

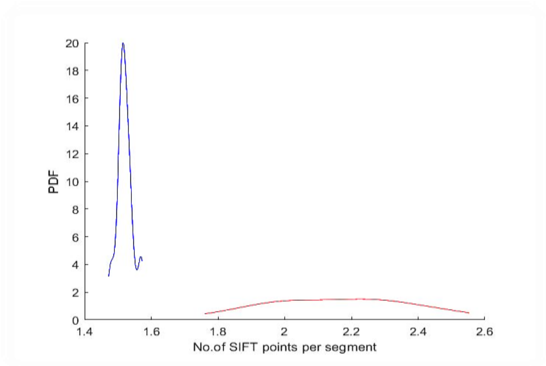
where TP is the true positives, FP is the false positives, FN is the false negatives, and TN is the true negatives and L is the data class length.

$FN = L - TP$ (12)

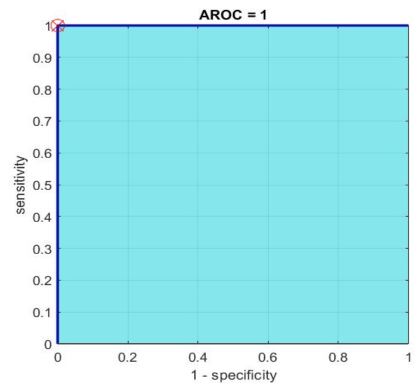
$$TN = L - FP \quad (13)$$

## 3. Simulation Results and Discussion

Simulation experiments have been carried out on the whole CHB-MIT dataset as tabulated in Table 1. For each case, we apply the FWHT to analyze the EEG signals in frequency domain. Two kinds of attributes are considered including, band power of (delta beta gamma and theta) brain waves activity and MCL attribute. Simulation results of the detection process for all patients are illustrated in Tables 3 to 8. The majority voting strategy is applied on the results of all attributes for efficient detection results. It is clear from all obtained results that the majority voting gives the best detection results. Moreover, working on MCL with FWHT gives the best results compared to the results obtained with other features achieving an average sensitivity of 98.59%, an average specificity of 96.26% and an average accuracy of 96,83%. Samples of MCL feature with the FWHT is illustrated in Figs.2, which indicates the PDFs and area under the ROC curve for all patients.

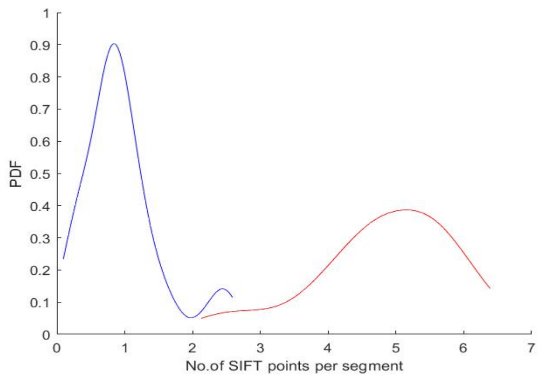



No. of Segments




PDF of patient 1 for mean curve length feature

AROC of patient 1for mean curve length feature

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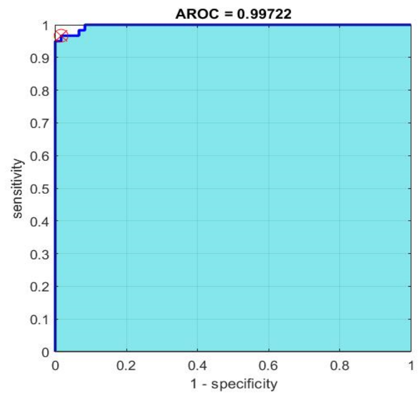
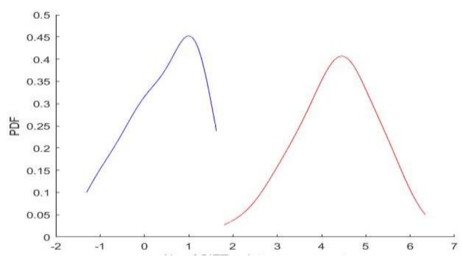
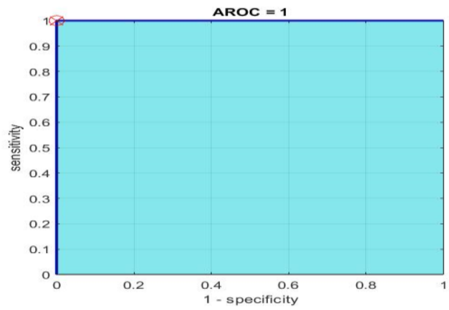



PDF of patient 2 for mean curve length feature




No. of Segments

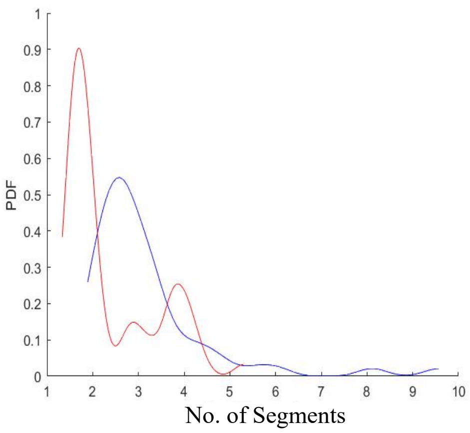
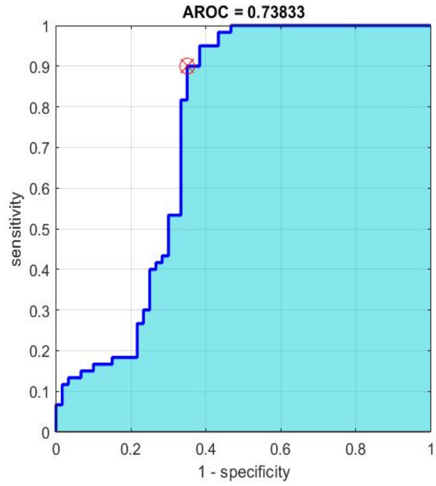
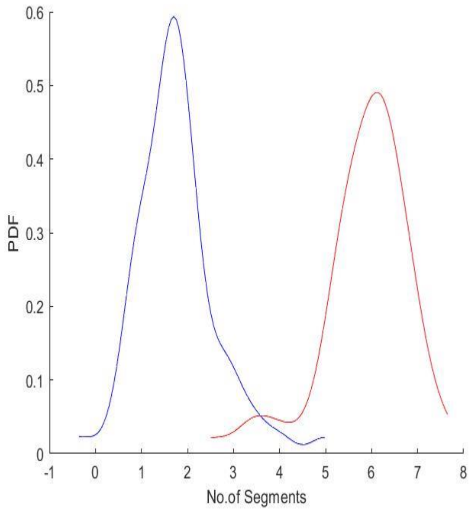
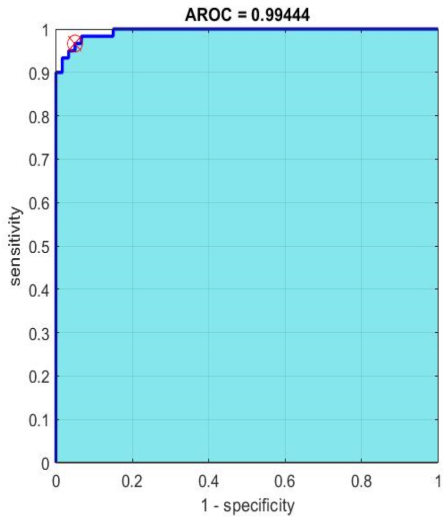
| | |
|---|---|
| | |
| PDF of patient 3 for mean curve length feature | AROC of patient 3 for mean curve length feature |
|   |   |
| PDF of patient 4 for mean curve length feature | AROC of patient 4 for mean curve length feature |
|   |   |
| PDF of patient 5 for mean curve length feature | AROC of patient 5 for mean curve length feature |

**Fig.3** PDFs and AROCs of samples patients for mean curve length feature

One of the advantages of the proposed approach is avoiding the over-training problem, which is a major concern in modeling of data in several fields due to using a statistical model that contains more parameters than can be justified by the data. Unlike other techniques, one of the reasons that make our approach far from the over-training is that we do not use a noisy or unknown dataset. The dataset we use is well prepared as a standard benchmark for many years of research. In addition, we do not have a training process in which over-training may occur, but it is a direct detection technique (online technique) based on different metrics, statistical analysis and similarity measures. It avoids the training process, testing and then over-training problem. However, the proposed approach lack of simultaneous localization in time and frequency domain as occurred in wavelet domain with various families of wavelets. [16]

In addition to the accuracy of the proposed approach in detecting epileptic seizures, it also saves a lot of time as it avoids the time consumed in the training process. In addition, the time of the proposed approach is very short ranging from 2 to 3 minutes using the same machine specifications. All of these benefits make the proposed approach more effective in comparison with other previous methods. A comparison study with the existing state-of-the-art algorithms is given in Tables 9.

**Table 3. Results of** band power (Beta) **with FWHT for all patients**

| For all Patient | Result of band power (Beta) with FWHT |
|---|---|
| Average SEN (%) | 95.50725 |
| Average SPE (%) | 94.5652 |
| Average AROC | 0.9461594 |
| Average ACC (%) | 94.02174 |
| Average PPV (%) | 93.10699 |
| Average NPV (%) | 84.47888 |

**Table 4. Results of** band power (Delta) **with FWHT for all patients**

| For all Patient | Result of band power (Delta) with FWHT |
|---|---|
| Average SEN (%) | 91.05263 |
| Average SPE (%) | 91 |
| Average AROC | 0.9163056 |
| Average ACC (%) | 91.1508 |
| Average PPV (%) | 92.13157 |
| Average NPV (%) | 89.38925 |

**Table 5. Results of** band power gamma **activity with FWHT for all patients**

| For all Patient | Result of band power gamma with FWHT |
|---|---|
| Average SEN (%) | 94.54545 |
| Average SPE (%) | 95.21738 |
| Average AROC | 0.9661353 |
| Average ACC (%) | 96.13636 |
| Average PPV (%) | 94.28802 |
| Average NPV (%) | 95.49344 |

**Table 6. Results of** band power theta **activity with FWHT for all patients**

| For all Patient | Result of band power theta with FWHT |
|---|---|
| Average SEN (%) | 94.4697 |
| Average SPE (%) | 94.34782 |
| Average AROC | 0.9589372 |
| Average ACC (%) | 94.0942 |
| Average PPV (%) | 92.83895 |
| Average NPV (%) | 86.25124 |

**Table 7. Results of mean curve length activity with FWHT for all patients**

| For all Patient | Result of MCL with FWHT |
|---|---|
| Average SEN (%) | 98.59206 |
| Average SPE (%) | 96.26984 |
| Average AROC | 0.9617989 |
| Average ACC (%) | 96.83333 |
| Average PPV (%) | 90.41736 |
| Average NPV (%) | 88.2364 |

**Table 8. Comparison of performance for the existing with the proposed method**

| Author | Dataset | Subject | Features | Classifier |
|---|---|---|---|---|
| Kostas M. Tsiouris et al. [17] | CHB-MIT | 24 patients 181 seizures | Spectral analysis, variation in EEG energy distribution over the delta, theta, and alpha rhythms | subset selection method (SSM) |
| Prathap et al. [18] | CHB-MIT | 17 patients 78 seizures | Spectral power and spectral power ratios | Kernel sparse representation classifier |
| Behnam et al. [19] | CHB-MIT | 23 patients 163 seizures | Arithmetic mean, geometric mean, variance, COV, mode, median, Pearson and Bowley's, and moment measure of skewness, kurtosis, and negative entropy | Bayesian classifier |
| Janjarasjitt et al. [20] | CHB-MIT | 12 patients | Wavelet-based spectral features | No classifier |
| Proposed Method | CHB-MIT | 23 patients 174 Seizures | Band power of (beta delta theta and gamma) and MCL activity | Thresholding strategy |

## 4. Conclusion

The proposed approach adopted in this paper depends on using the FWHT, and hence statistical analysis of decomposed coefficients. Different statistical attributes are estimated for them. A thresholding strategy is applied on each attribute. Hence, a decision is taken based on that attribute. The main advantage of this approach is the avoidance of the classification problems represented in training, testing and overfitting problems. In addition, the results prove that mean curve length with FWHT demonstrates the best performance in comparison.

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